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GRADIENT BOOSTING METHOD APPLICATION TO SUPPORT PROCESS DECISIONS IN THE ELECTRON-BEAM WELDING PROCESS

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The purpose of the study is to develop a technological process mathematical model of creating permanent joints of dissimilar materials based on electron-beam welding using machine learning algorithms. Each of the connected elements is a responsible unit of the complex device, due to this fact, strict criteria are set for the quality of the welded joint. In essence, the set task is a regression task. There are many algorithms suitable for solving the regression problem. However, often the use of one algorithm does not provide sufficient accuracy of the result. One way to solve this problem is to develop a composition of algorithms to compensate for the problems of each of them. One of the most effective and potent compositional algorithms is the gradient boosting algorithm. This algorithm use will improve the quality of the regression model. The proposed model will allow the technologist to set the process parameters and to get an assessment of the final product quality, as well as by setting input and output values. The use of assessment methods and forecasting will reduce the time and labor costs of searching, developing and adjusting the process. A description of the gradient boosting algorithm is given, as well as an analysis of the applicability of this algorithm to the model and a conclusion regarding the areas of its applicability and the reliability of the forecasts obtained by its direct use. In addition, we consider the process of direct model training based on the data obtained as part of search experiments to improve the quality of final product. The results of the applicability analysis allow us to judge the admissibility of using the proposed method for processes that have similar statistical dependencies. The application of the proposed approach will make it possible to support the adoption of technological decisions by specialists in electron-beam welding during the development of the technological process and when new types of products are put into production.

Keywords: electron-beam welding, technological process, experiments, gradient boosting, machine learning.

ПРИМЕНЕНИЕ МЕТОДА ГРАДИЕНТНОГО БУСТИНГА ДЛЯ ПОДДЕРЖКИ ПРИНЯТИЯ ТЕХНОЛОГИЧЕСКИХ РЕШЕНИЙ В ПРОЦЕССЕ ЭЛЕКТРОННО-ЛУЧЕВОЙ СВАРКИ

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Целью исследования является создание математической модели технологического процесса изготовления неразъемных соединений разнородных материалов на основе электронно-лучевой сварки с использованием алгоритмов машинного обучения. Каждый из соединяемых элементов представляет собой ответственный узел комплексного устройства, в связи с чем выставляются жесткие критерии к качеству сварного соединения. В сущности, поставленная задача представляет собой задачу регрессии. Существует множество алгоритмов, подходящих для решения задачи регрессии. Однако зачастую использование одного алгоритма не обеспечивает достаточной точности полученного результата. Одним из способов решения такой проблемы является построение композиции алгоритмов для компенсации проблем каждого из них. Одним из наиболее эффективных и мощных алгоритмов композиции является градиентный бустинг. Использование данного алгоритма повысит качество модели регрессии. Предлагаемая модель позволит технологу задавать параметры технологического процесса и получать оценку качества конечного изделия равно как по заданию входных, так и выходных величин. Использование методов оценки и прогнозирование снизит временные и трудовые затраты на поиск, отработку и наладку технологического процесса. Приводится описание алгоритма градиентного бустинга, а также анализ применимости данного алгоритма к модели, равно как и заключение касательно *областей его применимости и достоверности прогнозов, получаемых при его использовании. Кроме того, рассматривается процесс непосредственного обучения модели на основе данных, полученных в рамках проведения поисковых экспериментов для улучшения качества конечного изделия. Результаты анализа применимости позволяют судить о допустимости использования предложенного метода для процессов, имеющих схожие статистические зависимости. Применение предложенного подхода позволит осуществить поддержку принятия технологических решений специалистов по электронно-лучевой сварке при отработке технологического процесса и при вводе в производство новых видов продукции.*

Ключевые слова: электронно-лучевая сварка, технологический процесс, эксперименты, градиентный бустинг, машинное обучение.

Introduction. For a number of technological processes the issue of selecting or conscious choosing optimal parameters that depend on the quality criteria applied to the final product is acute [1–5]. Moreover, this statement is also true for ways to search for improvement or transformation of an already established technological process. For example, when you need to improve one of the parameters that determine the quality of the final product, without changing the others, or without allowing them to deviate by a certain amount. However, some processes, such as electron-beam welding [6; 7] are relatively difficult to adjust or change, due to either insufficient knowledge or integrated complexity, when it is impossible to take into account all factors in a way that would allow us to uniquely determine the potential changes and the impact of parameters on the process as a whole. This leads to the need to search for methods to simplify the process of setting up and converting technological processes.

Considering the technological process as a closed system with different input and output parameters, you can build an appropriate model and then use it as a tool for forecasting and optimization. The purpose of this research was to study one of the machine learning algorithms as a subject for creating a complex mathematical model that would allow forming a conscious view of the choice of process parameters in both local and global search for the optimum determined by the technologist. This approach will significantly reduce the time to set up the technological process, as well as the cost of research, which will ultimately have a positive impact on the cost and quality of products.

In essence, the task is a regression task. One of the most effective and potent composition algorithms is the gradient boosting algorithm [8–13]. The use of the proposed mathematical model will improve the quality of control of the electron-beam welding process by implementing support for technological decision-making using the gradient boosting algorithm. In the future, this approach can be used for technological processes that have similar statistical dependencies.

Description of the training data set. As the initial data, the results of experimental studies conducted to improve the technological process of electron-beam welding of a product, the assembly of which consists of elements consisting of dissimilar material, were used. The electron beam welding unit where the research was conducted is designed for electron-beam welding in high vacuum of assembly units parts made of stainless steels, titanium, aluminum and special alloys. The existing unit of electron beam welding provides repeatability of modes within the capabilities of the implemented control system. Welding operations were performed on simulators corresponding to the technological product. To reduce energy input during welding:

1. The welding current value decreased (IW).
2. The current focus of the electron beam increased (IF).
3. The welding speed increased (VW).
4. The distance from the surface of the samples to the electron-optical system changed (FP).

According to the set of technological modes parameters, the minimum possible sizes of welding seams were provided: the depth of the seam (Depth) and the width of the seam (Width).

During the research, electron-beam welding of 18 samples was performed. The results of metallographic control on the size of the welding seam for each sample were carried out in 4 cross-sections of the welding seam. The accelerating voltage was constant in the range of 19.8–20 kV. The obtained data set is collected as a part of welding modes, sizes of welding seams in cross sections of all samples. Statistical indicators of the training data set are shown in tab. 1.

Mathematical statement of the problem. The formal statement of the supporting technological decision-making problem in the process of electron-beam welding is a regression problem, in which the characteristics of the welded joint must be predicted based on a set of the technological process initial parameters. The mathematical statement of the control problem in this case will be the following. Let there be a set of process parameters: IW – welding current value, IF – electron beam focusing current, VW – welding speed, FP – distance from the sample surface to the electron-optical system, Depth – weld depth, Width – weld width. There is an unknown target mapping dependency: y*: (IW, IF, VW, FP) → (Depth, Width), the value of which is known only in the training sample. You need to develop a mapping algorithm.

As part of this work, we have:

1. Data set: $L = \{x_i, y_i\}$, $i = 1 \ldots n$, where:

– x_{iw} – welding current, mA;

– x_{if} – focusing current, mA;

– x_{vw} – welding speed, r/min;

– x_{fp} – distance to Electron Optical Welding System (EOWS), mm;

– y_{depth} – weld depth;

– y_{width} – weld width;

– x belongs to Q^4, y belongs to Q^2, where Q is the set of positive rational numbers.

2. Model $f(X)$, which predicts the values for each object, where X is the technological process parameters, in this case, the technological parameters of electron

beam-welding. To evaluate the quality of the model $f(X)$, the following metrics are used: mean square error (MSE); mean absolute error (MAE); coefficient of determination R^2 (R2).

In this research, $f(x)$ is an ensemble of «Gradient Boosting» models (Gradient Boosting Regressor).

Gradient Boosting. The Gradient Boosting Regressor model was implemented using the scikit-learn 0.22.2 package in Python 3.8 [14; 15]. Boosting is a technique for constructing ensembles, in which predictors are not built independently, but sequentially. This technique uses the idea that the next model will learn from the mistakes of the previous one. They have an unequal probability of appearing in subsequent models, and those that give the greatest error are more likely to appear [16]. The algorithm is Gradient boosting:

1. Initialize the model with a constant value

$$\hat{f}(x,0)=\hat{f}_0, \hat{f}_0 = y, y \in \mathbb{R}:$$

$$\hat{f}_0 = \arg\min_{y} \sum_{i=1}^{n} L(y_i, y).$$

2. For each iteration t = 1…M (M = n_estimators) repeat:

a) count the pseudo-remains r_{it}

$$r_{it} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=\hat{f}(x,t-1)}, \quad i = 1,...,n;$$

b) build a new algorithm $h_t(x)$ as a regression on pseudo-residues

$$\{(x_i, r_{it})\}_{i=1...n};$$

c) find the optimum ratio of p_t when $h_t(x)$ relative to the original loss function:

$$\rho_t = \arg\min_{\rho} \sum_{i=1}^{n} L(y_i, \hat{f}(x_i, t-1) + \rho \cdot h(x_i, \theta));$$

d) record the model:

$$\hat{f}_t(x) = \rho_t \cdot h_t(x);$$

e) update the current approximation:

$$\hat{f}(x,t) = \hat{f}(x,t-1) + \hat{f}_t(x) = \sum_{i=0}^{t} \hat{f}_i(x)$$

3. Build the final model:

$$f(x) = \sum_{i=0}^{M} \hat{f}_i(x).$$

In this work, gradient boosting is implemented over the decision trees. This implementation of gradient boosting allows you to build a model in the form of a weak predictive models ensemble of decision trees.

In scikit-learn, the Gradient Boosting Regressor model builds the model in stages, which allows you to optimize arbitrary differentiable loss functions. At each stage, the decision tree corresponds to the negative gradient of the specified loss function. The main parameters in Gradient Boosting Regressor that were selected to find the optimal solution:

1) n_estimators – the number of steps to increase the gradient (the number of weak decision trees used);

2) loss – loss function for optimization. (MSE, MAE);

3) max_depth – maximum depth of each decision tree;

4) max_features – the number of features by which the split is searched;

5) min_samples_split – the minimum number of objects required to split the internal node of the tree;

6) min_samples_leaf — the minimum number of objects in the leaf.

Selection of optimal parameters for the model. The GridSearchCV function, which is part of the scikit-learn module, was used to select the optimal parameters in the model. The GridSearchCV function implements an exhaustive search for the specified parameter values for the model. This function implements the „selection" and „assessment" methods.

Model parameters are optimized by cross – validation over the parameter grid.

Main parameters of the GridSearchCV function:

1) estimator – the model in which the selection happens;

2) param_grid – sets of hyper-parameters that need to be checked;

3) scoring – the metric that will be used for assessment;

4) cv – the number of blocks in cross-validation.

Experimental research.

Experiment setup. The model was set up and trained separately for each: y_{depth} and y_{width}, on a set of X parameters. Training a model with optimal parameters on a full dataset is designated as train_score. To check the accuracy of the model prediction (cv_score), the cross-validation was used. To get an estimate by cross-validation, the cross_val_score function from the scikit-learn module is used.

Table 1

Statistical indicators of the training data set

Indicator	IW	IF	VW	FP	Depth	Width
Number	72	72	72	72	72	72
Sample mean	45.666	141.333	8.639	78.333	1.196	1.970
Mean square deviation	1.678	5.146	2.061	21.494	0.225	0.279
Minimum	43	131	4,5	50	0.80	1.68
25 %	44	139	8	60	1.08	1.76
50 %	45	141	9	80	1.20	1.84
75 %	47	146	10	80	1.29	2.05
Maximum	49	150	12	125	1.76	2.60

Table 2

The best results of selection of model parameters for the depth of the seam

n_estimators	loss	max depth	max features	min samples leaf	min samples split	mean_test_score
100	MSE	3	2	1	5	0.050862
90	MSE	3	2	1	5	0.050887
80	MSE	3	3	1	5	0.050893
80	MSE	3	2	1	5	0.050893
80	MSE	3	4	1	4	0.050893
100	MSE	3	3	1	5	0.050896
90	MSE	3	3	1	2	0.050898
80	MSE	3	4	1	2	0.050899
80	MSE	3	4	1	3	0.050899
100	MSE	3	3	1	2	0.050900

The number of blocks in cross-validation is 4. To improve the accuracy of the check, the algorithm is performed:

For each $i = 1, \ldots, K$:

1. Randomly shuffle the *dataset– DS_i*.
2. Get the score using *cross_val_score* on $DS_i - S_i$.
3. The final score is the average:

$$cv\_score_K = \frac{1}{K}\sum_{i=1}^{K} S_i$$

The number of K is selected in this way until:

$$cv\_score_K - cv\_score_{K-1} \leq 0.1 .$$

Selection of parameters for the Gradient Boosting Regressor (GBR) model.

The model for the seam depth. Model hyper-parameters were selected among the following values:

1. n_estimators: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100;
2. loss: MSE, MAE;
3. max_depth: 1, 2, 3, 4;
4. max_features:1, 2, 3, 4;
5. min_samples_leaf: 1, 2, 3, 4;
6. min_samples_split: 2, 3, 4, 5.

The search for optimal hyper-parameters was carried out using *GridSearchCV*, where the average absolute error (MAE) was used as a metric for evaluating each test, and the number of blocks in the cross-validation is 5.

The best ten results, in descending order, are shown in tab. 2.

In tab. 2 the following notations are used: mean_test_score – the average value of the test score.

When fixing the values (loss = MSE, max_depth = 3, max_features = 2, min_samples_leaf = 1, min_samples_split = 5), n_estimators change graphs were built (fig. 1).

When fixing values (n_estimators = 100, loss = MSE, max_features = 2, min_samples_leaf = 1, min_samples_split = 5), the max_depth change graphs were built (fig. 2).

When fixing values (n_estimators = 100, loss = MSE, max_depth = 3, max_features = 2, min_samples_leaf = 1), the graphs of min_samples_split were changes built (fig. 3).

As shown in fig. 3, the best score on the test was min_samples_split = 7.

Best hyper-parameters: n_estimators = 100, loss = MSE, max_depth = 3, max_features = 2, min_samples_leaf = 1, min_samples_split = 7.

The importance of technical parameters is distributed as follows: x_{iw} – 6 %; x_{if} – 26 %; x_{vw} – 44 %; x_{fp} – 24 %.

Tab. 3 presents the scores of the mathematical model for the depth of the weld.

Table 3

The scores of a mathematical model for the depth of the welding seam

Scores	R2	MAE
train_score	0.932651	0.042958
cv_score	0.896255	0.044262

The search for optimal hyper-parameters was carried out using *GridSearchCV,* where the metric is the MAE used to assess each test, and the number of blocks in cross-validation is 5.

The top ten results, in descending order, are shown in tab. 4.

The following notations are used in tab. 4: mean_test_score – the average value of the test score.

When fixing the values (loss = MSE, max_depth = 3, max_features = 3, min_samples_leaf = 1, min_samples_split = 4), the n_estimators change graphs were built (fig. 4).

When fixing values (n_estimators = 100, loss = MAE, max_features = 3, min_samples_leaf = 1, min_samples_split = 4), the max_depth change graphs were built (fig. 5).

When fixing values (n_estimators = 100, loss = MAE, max_depth = 3, max_features = 3, min_samples_leaf = 1), the graphs of min_samples_split changes were built (fig. 6).

Best hyper-parameters: n_estimators = 100, loss = MAE, max_depth = 3, max_features = 3, min_samples_leaf = 1, min_samples_split = 4.

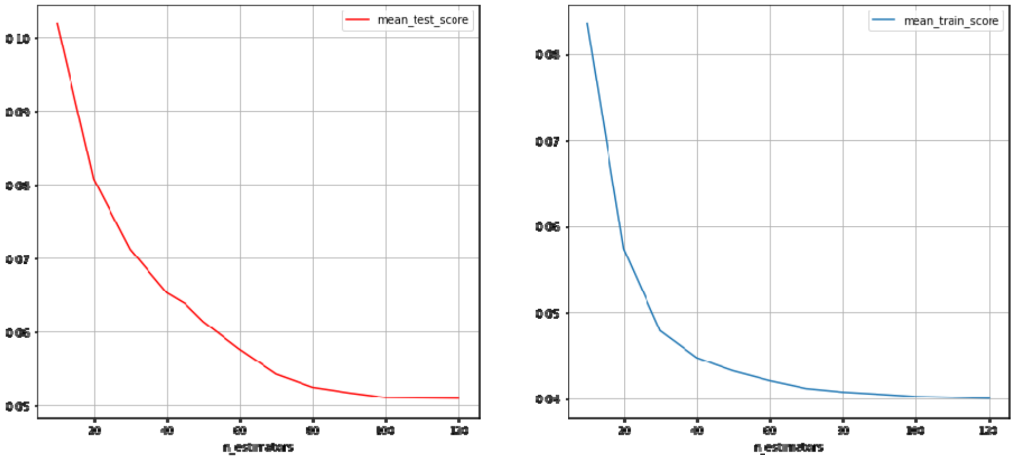

Fig. 1. The changes of n_estimators parameter

Рис. 1. Изменения параметра n_estimators

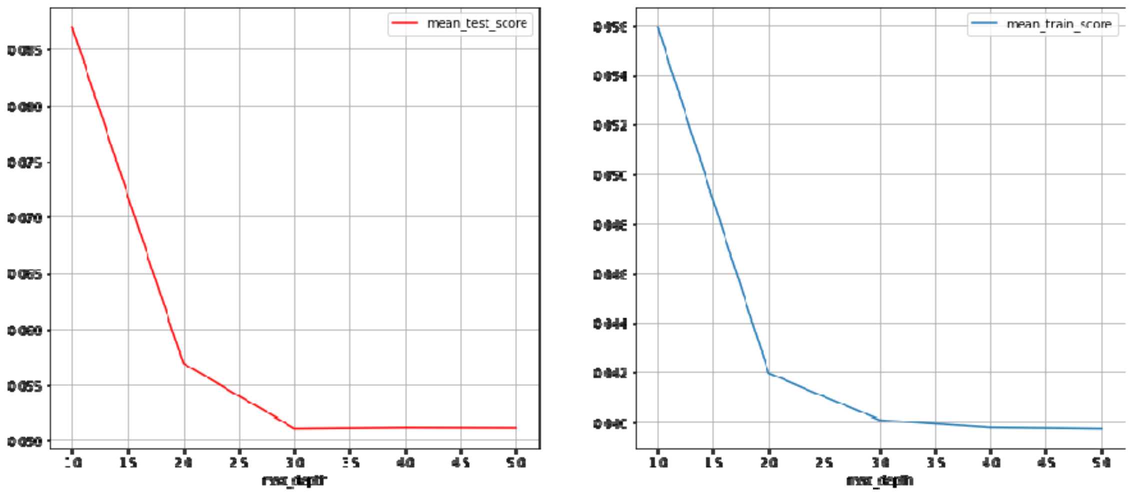

Fig. 2. The changes of max_depth parameter

Рис. 2. Изменения параметра max_depth

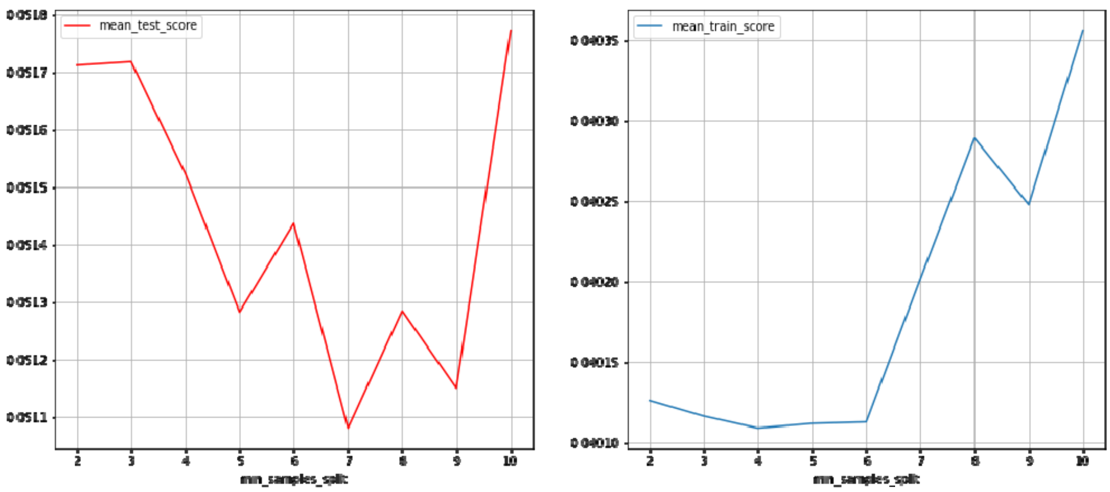

Fig. 3. The changes of min_samples_split parameter

Рис. 3. Изменения параметра min_samples_split

Table 4

The best results of selection of model parameters for the width of the seam

n_estimators	loss	max depth	max features	min samples leaf	min samples split	mean_test_score
100	MAE	3	3	1	4	0.030108
80	MAE	3	3	1	4	0.030112
90	MAE	3	3	1	4	0.030166
70	MAE	3	3	1	4	0.030391
100	MAE	3	3	1	5	0.030459
80	MAE	3	3	1	5	0.030475
90	MAE	3	3	1	5	0.030509
80	MAE	3	3	1	3	0.030615
80	MAE	3	3	1	2	0.030615
60	MAE	3	3	1	4	0.030649

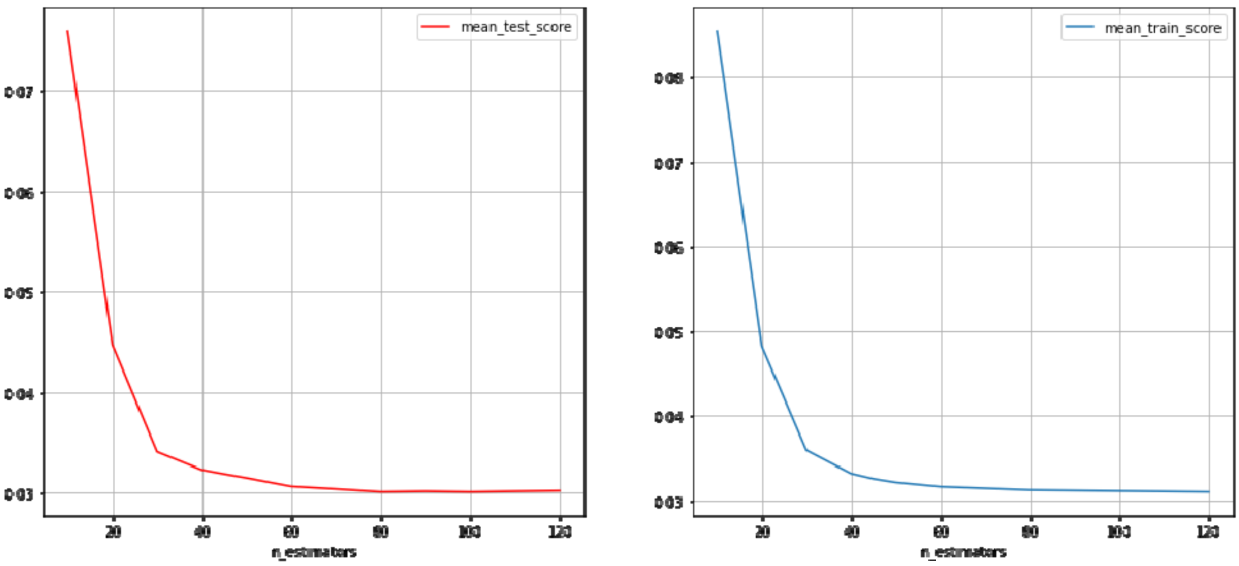

Fig. 4. The changes of n_estimators parameter

Рис. 4. Изменения параметра n_estimators

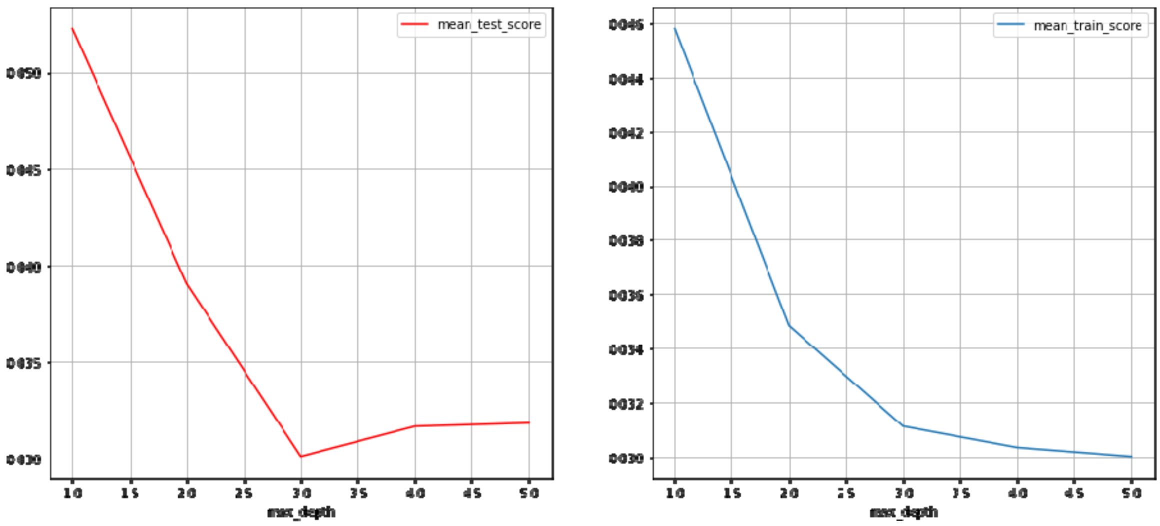

Fig. 5. The changes of max_depth parameter

Рис. 5. Изменения параметра max_depth

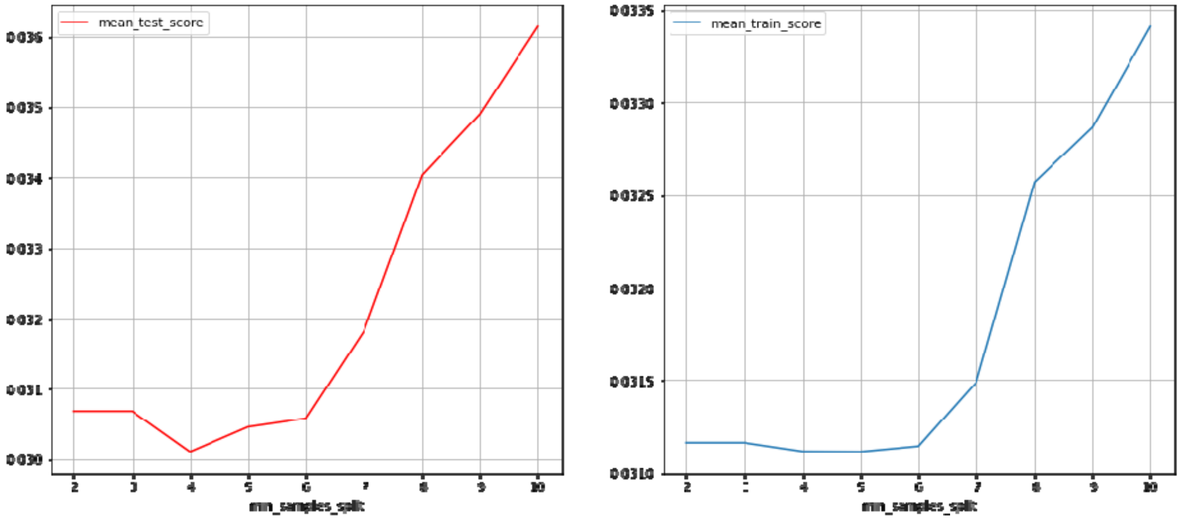

Fig. 6. The changes of min_samples_split parameter

Рис. 6. Изменения параметра min_samples_split

The importance of technical parameters is distributed as follows: x_{iw} – 13 %; x_{if} – 41 %; x_{vw} – 33 %; x_{fp} – 13 %.

Tab. 5 shows the results of evaluations.

Table 5

Model scores by the width of the weld

Scores	R2	MAE
train_score	0.970136	0.030648
cv_score	0.960603	0.040242

Results. In this research the mathematical models based on gradient boosting according to the training set data (dataset) were considered.

The following best parameters of the mathematical model are obtained:

1. For the seam depth: n_estimators = 100, loss = MSE, max_depth = 3, max_features = 2, min_samples_leaf = 1, min_samples_split = 7.

2. For the seam width: n_estimators = 100, loss = MSE, max_depth = 3, max_features = 3, min_samples_leaf = 1, min_samples_split = 4.

The scores of the finished models are shown in tab. 6.

Table 6

Model scores when testing cv_score

Model	R2	MAE
Depth	0.896255	0.044262
Width	0.960603	0.040242

As can be seen from the scores of the mathematical model based on gradient boosting, the proposed model is able to solve the problem of supporting technological decision-making based on gradient boosting with a fairly low value of the average absolute error and a high value of the coefficient of determination.

Conclusion. As a result of the research, the analysis of the applicability of the Gradient Boosting Regressor method as a basis for creating a mathematical model for optimizing and forecasting the process of electron-beam welding was performed. Based on the obtained model scores we can judge the feasibility of using the proposed approach to support technological decision-making in the technological processes control that have similar statistical dependencies.

The obtained model allows us to support technological decision-making in the process of electron-beam welding of dissimilar materials with high accuracy. The use of the technique will improve the quality of the electron-beam welding process control. The results of this study are planned to be used in further research designed to support decision-making in relation to other technological processes that have similar statistical dependencies.

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References

1. Braverman V. Ya., Belozertsev V. S., Litvinov V. P., Rozanov O. V. [Issues of managing weld formation in electron beam welding]. *Sibirskiy zhurnal nauki i tekhnologiy*. 2008,. Vol. 2 (19), P. 148–152 (In Russ.).

2. Weglowski M. S., Blacha S., Phillips A. Electron beam welding – Techniques and trends – Review. Vacuum. 2016, Vol. 130, P. 72–92.

3. Zlobin S. K., Mikhnev M. M., Laptenok V. D., Seregin Yu. N., Bocharov A. N., Tynchenko V. S.,

Dolgopolov B. B. [Automated equipment and technology for soldering waveguide paths of spacecraft]. *Sibirskiy zhurnal nauki i tekhnologiy*. 2014, No. 4 (56), P. 219–229 (In Russ.).

4. Murygin A. V., Tynchenko V. S., Laptenok V. D., Emilova O. A., Seregin Y. N. Modeling of thermal processes in waveguide tracts induction soldering. *IOP Conference Series: Materials Science and Engineering*. 2017, Vol. 173, No. 1, P. 012026.

5. Aydin K., Kaya Y., Kahraman N. Experimental study of diffusion welding/bonding of titanium to copper. *Materials & Design*. 2012, Vol. 37, P. 356–368.

6. Kurashkin S. O., Tynchenko V. S., Seregin Y. N., Petrenko V. E., Milov A. V., Murygin A. V. Mathematical models of beam input and output in the process of electron beam welding of thin-walled structures. *Journal of Physics: Conference Series.* 2020, Vol. 1515, P. 052048.

7. Tynchenko V. S., Milov A. V., Bukhtoyarov V. V., Kukartsev V. V., Tynchenko V. V., Bashmur K. A. The concept of an electron beam I/O control system to optimize the weld formation in the process of electron beam welding. *Journal of Physics: Conference Series.* 2019, Vol. 1399, No. 4, P. 044092.

8. Duffy N., Helmbold D. Boosting methods for regression. *Machine Learning.* 2002, Vol. 47, No. 2–3, P. 153–200.

9. Goodfellow I., Bengio Y., Courville A. Deep learning. Cambridge, MA, MIT press, 2016, 318 p.

10. Son J., Jung I., Park K., Han B. Tracking-by-segmentation with online gradient boosting decision tree. *Proceedings of the IEEE International Conference on Computer Vision*. 2015, P. 3056–3064.

11. Peter S., Diego F., Hamprecht F. A., Nadler B. Cost efficient gradient boosting. Advances in Neural Information Processing Systems. 2017, P. 1551–1561.

12. Salakhutdinova K. I., Lebedev I. S., Krivtsova I. Ye. [Gradient boosting algorithm for decision trees in the software identification problem]. *Nauchno-tekhnicheskiy vestnik informatsionnykh tekhnologiy, mekhaniki i optiki.* 2018, Vol. 18, No. 6, P. 1016–1022 (In Russ.).

13. Dyakonov I. D., Novikova S. V. [Solution of the forecasting problem with the help of gradient boosting over decision trees]. *Nauchnyy forum: Tekhnicheskiye i fiziko-matematicheskiye nauki.* 2018, P. 9–12.

14. Pedregosa F., Varoquaux G., Gramfort A., Michel V., Thirion B., Grisel O., Vanderplas J. Scikit-learn: Machine learning in Python. *The Journal of Machine Learning research.* 2011, Vol. 12, P. 2825–2830.

15. VanRossum G., Drake F. L. The python language reference. Amsterdam, Netherlands, Python software foundation. 2010, 162 p.

16. Schapire R. E., Freund Y. Boosting: Foundations and algorithms. *Kybernetes.* 2013, Vol. 42, No. 1, P. 164–166.

Библиографические ссылки

1. Вопросы управления формированием сварного шва при электронно-лучевой сварке / В. Я. Браверман, В. С. Белозерцев, В. П. Литвинов и др. // Сибирский журнал науки и технологий. 2008. № 2 (19). С. 148–152.

2. Weglowski M. S., Blacha S., Phillips A. Electron beam welding – Techniques and trends –Review // Vacuum. 2016. Vol. 130. P. 72–92.

3. Автоматизированное оборудование и технология для пайки волноводных трактов космических аппаратов / С. К. Злобин, М. М. Михнев, В. Д. Лаптенок и др. //Сибирский журнал науки и технологий. 2014. №. 4 (56). С. 219–229.

4. Modeling of thermal processes in waveguide tracts induction soldering / A. V. Murygin, V. S. Tynchenko, V. D. Laptenok et al. // IOP Conference Series: Materials Science and Engineering, 2017. Vol. 173, No. 1. P. 012026.

5. Aydin K., Kaya Y., Kahraman N. Experimental study of diffusion welding/bonding of titanium to copper // Materials & Design. 2012. Vol. 37. P. 356–368.

6. Mathematical models of beam input and output in the process of electron beam welding of thin-walled structures / S. O. Kurashkin, V. S. Tynchenko, Y. N. Seregin et al. // Journal of Physics: Conference Series. 2020. Vol. 1515. P. 052048.

7. The concept of an electron beam I/O control system to optimize the weld formation in the process of electron beam welding / V. S. Tynchenko, A. V. Milov, V. V. Bukhtoyarov et al. // Journal of Physics: Conference Series. 2019. Vol. 1399, No. 4. P. 044092.

8. Duffy N., Helmbold D. Boosting methods for regression // Machine Learning. 2002. Vol. 47, No. 2–3. P. 153–200.

9. Goodfellow I., Bengio Y., Courville A. Deep learning. Cambridge, MA: MIT press, 2016. 318 p.

10. Tracking-by-segmentation with online gradient boosting decision tree / J. Son, I. Jung, K. Park et al. // Proceedings of the IEEE International Conference on Computer Vision. 2015. P. 3056–3064.

11. Cost efficient gradient boosting / S. Peter, F. Diego, F. A. Hamprecht et al. // Advances in Neural Information Processing Systems. 2017. P. 1551–1561.

12. Салахутдинова К. И., Лебедев И. С., Кривцова И. Е. Алгоритм градиентного бустинга деревьев решений в задаче идентификации программного обеспечения // Научно-технический вестник информационных технологий, механики и оптики. 2018. Т. 18, №. 6. С. 1016–1022.

13. Дьяконов И. Д., Новикова С. В. Решение задачи прогнозирования при помощи градиентного бустинга над решающими деревьями // Научный форум: технические и физико-математические науки. 2018. С. 9–12.

14. Scikit-learn: Machine learning in Python / F. Pedregosa, G. Varoquaux, A. Gramfort et al. // The Journal of Machine Learning research, 2011. Vol. 12. P. 2825–2830.

15. VanRossum G., Drake F. L. The python language reference. Amsterdam, Netherlands : Python software foundation. 2010. 162 p.

16. Schapire R. E., Freund Y. Boosting: Foundations and algorithms // Kybernetes. 2013. Vol. 42, No. 1. P. 164–166.

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